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MODELING THE EMPLOYMENT RATE IN RUSSIA: A SPATIAL-ECONOMETRIC APPROACH [1]

The purpose of this study is to identify factors that affect the level of employment in Russian regions. However, Russia is not a homogeneous country, and this effect may not be the same for all regions. That is why we split the regions of Russia into three groups, depending on the state of the labor market in this and neighboring regions. The HH (high-high) group comprises regions with a favorable situation in their labor markets, and which are also surrounded mostly by prosperous regions. Two groups of regions with a less favorable situation are located respectively in the south of Russia (LL1, low-low group 1) and southern Siberia and Zabaikalye (LL2, low-low group 2). We considered the twelve-year period from 2005 to 2016. As explanatory variables, we used variables for the attractiveness of the region, demographic characteristics of the region, and the degree of diversity of employees by economic activities. We tested hypotheses about differences in 1) the spatial effects and 2) the impact of the various explanatory variables for these groups of variables. To test our main hypotheses, we used spatial regression dynamic models estimated with the help of the generalized method of moments. Both main hypotheses received empirical confirmation. Spatial effects were different. The regions of the LL2 group are not affected by the situation in other local markets; regions of LL1 and HH groups are affected by the rest of Russia's regions, and the extent of this influence decreases with the increase in geographical distance between regions. Moreover, the regions of the LL1 group compete with neighboring regions: if the situation in one of them improves, then it draws on the resources of the others. Regarding the impact of the explanatory variables, the "group effect" was revealed for the variables: share of urban population, net migration rate, shares of people below and above working age, share of people with higher education. Our results can favor the better design of national and regional policies to improve labor market performance in Russia based on the heterogeneity of the Russian regions.

Keywords: employment, labor market, regional data, spatial effects, spatial models, labor policies, development policies

1. Introduction

The socio-economic development plan for the Russian Federation until 2020 states that the priorities of the state regional policy are (i) balanced socio-economic regional development, and (ii) the reduction of interregional disparities.

So, knowing how regions are distributed into high or low employment groups/clusters is a key empirical issue with significant policy implications. However, according to [1] Oschepkov and Kapelyushnikov (2015), there is no single joint Russian labor market; instead, there is a system of rather weak interrelated territorial/local labor markets. The reasons are mainly the low mobility of the Russian population and significant differences among regions located in different parts of Russia. The authors also note that there are two groups of regions that were quite stable in the time interval 2000–2014: "leaders" (with high employment, low unemployment, and high wages) and "outsiders" (with low employment, high unemployment, and low wages).

In our research, we sought to determine, by means of a dynamic spatial econometric approach, which factors affect one of the most important indicators of labor markets: the level of employment of the population. The focus was on the mutual influence of regions on each other. If we did not take account of such influence in the models used, we might have encountered the problem of shifting estimates due to the omission of an essential variable. At the same time, it was difficult to take account of the influence of regions on each other; in this case, the number of model parameters that would have to be estimated would exceed the number of observations. However, there are spatial-econometric models that enable the use of several parameters to take the mutual influence of regions into account.

In the next section, we provide a brief overview of the key theoretical aspects and the main literature on regional aspects of the Russian labor market. In the third section, we describe the distinction of Russian regions into groups using Moran plots and the "leader-outsider" approach, present our data sources, discuss the choice of explanatory variables, and state the main research hypotheses. In the fourth section, we describe the methodology of econometric modeling. The sixth section sets out the results of the estimation and their interpretation. The last section contains some concluding remarks and policy implications.

2. The Theoretical Aspects and Literature Review

An original feature of this paper is its use of the employment rate and not the more traditional unemployment rate indicator. Here we briefly provide a short theoretical explanation for this choice.

Although the unemployment rate is still adopted in both theoretical and empirical studies, a growing number of economists have shown the key importance of the employment rate and its relative advantages with respect to the unemployment rate, especially because of the difficulties with this latter indicator in clearly defining the "active search for a job" as the crucial feature distinguishing unemployed people from inactive ones. In addition, some international institutions have started to define key policy objectives in terms of employment rates; the main example is the European Union that, within the framework of the European Employment Strategy, in 2000 at the Lisbon Council defined total and female employment rates as the labor market's performance objectives, and a similar employment rate index has been confirmed with the "Europe 2020" strategy launched in 2010.

It should be stressed that the level and dynamic of the employment rate cannot be simply derived from the level and dynamic of the unemployment rate. Let us consider the relationship between the two labor market performance indicators. First, we define the unemployment rate (*UR*) as the percentage ratio between the number of unemployed person *U* (i.e. unemployed people actively searching for a job) and the labor force *LF* (i.e. employed plus unemployed persons); second, we define the employment rate (*ER*) as the percentage ratio between the employed persons (*E*) and the working age population P_{15-72}; third, we define the participation rate (*PR*) as the percentage ratio between labor force (*LF*) and the working age population P_{15-72}.

$$UR = \frac{U \times 100}{LF}, \tag{1}$$

$$ER = \frac{E \times 100}{P_{15-72}}, \tag{2}$$

$$PR = \frac{LF \times 100}{P_{15-72}}. \tag{3}$$

Starting from equations (1), (2) and (3), the employment rate can be redefined as the complement to one of the unemployment rate (divided by 100) multiplied by the participation rate:

$$ER = \frac{E \times 100}{P_{15-72}} = \frac{LF - U}{LF} \times \frac{LF \times 100}{P_{15-72}} = \left(1 - \frac{UR}{100}\right) \times PR. \tag{4}$$

From equation (4), we can derive the unemployment rate (*UR*) as the complement to one of the ratios between employment rate (*ER*) and participation rate (*PR*) (the result multiplied by 100).

$$UR = \left(1 - \frac{ER}{PR}\right) \times 100. \tag{5}$$

Considering equation (5), a complex relationship emerges between the unemployment and employment rates; in fact, for example, a reduction in the unemployment rate is compatible with a reduction in the employment rate if the absolute value of this latter is lower than the absolute value of the reduction in the participation rate. Hence, it is not surprising that the unemployment rate can have different dynamics over time with respect to the employment rate.

For the reasons above mentioned, we adopted the employment rate as the key indicator of labor market performance in our study applied to Russian regions.

A growing body of literature investigates labor market performance at regional (sub-national) level, especially in large countries. In particular, the mutual influence of regions on each other in modeling the unemployment rates of regions in one or several countries is more often taken into account with the help of spatial-econometric models ([2] Caroleo and Pastore, 2010; [3] Mussida and Pastore, 2015, [4] Dolton et al., 2015; [5] Vega and Elhorst, 2016; [6] Manning and Petrongolo, 2017). There are several studies on the European regions, like [7] Head and Thierry (2006), [8] Ketterer and Rodríguez-Pose (2016). Some authors note the heterogeneity of the labor market and often identify clusters of regions, or they use 'core-periphery' models. However, there are fewer papers devoted to the regional labor market in transition countries. A review can be found in [9] Huber (2007) and [10] Bah and Brada (2014). Russia is an example of such a country.

According to [3] Pastore and Missuda (2015, introduction), "the Russian case seems to be specific and interesting not only among other transition countries but also in the European perspective". [11] Vakulenko and Gurvich (2016) highlight that "high wage flexibility is an important salient feature of the Russian labor market"; [12] Kapelyushnikov et al. (2012) argue that the current model of labor relations in Russia is a combination of very formal rules embodied in the Labor Code and a great variety of informal arrangements that make it feasible to relax those rules. This is a substantially flexible system.

In the case of Russia, from a regional perspective, issues related to economic growth have been studied more extensively ([13] Solanko, 2008; [14] Ledyaeva et al., 2008, [15] Kholodilin et al., 2012; [16] Akhmedjonov et al., 2013; [17] Lehmann and Silvagni, 2013; [18] Dolinskaya, 2002).

Almost all the available studies on regional labor markets examine unemployment rates ([19] Demidova and Signorelli, 2012, [20] Demidova et al., 2013, [21] Demidova et al., 2015, [22] Blinova et al., 2015, [23] Blinova et al., 2016, [24] Rusanovskiy and Markov, 2016). Hence, there is a lack of studies modeling regional employment rates. The exception is the work of [1] Oschepkov and Kapelyushnikov (2015) mentioned above, in which the authors come to the following conclusions: (i) regional labor markets in Russia converge; (ii) both regions-"leaders" and regions-"outsiders" tend to form clusters of nearby or adjacent regions. Thus, it makes sense to try to identify such clusters. [25] Danilenko et al. (2017) attempt to reveal clubs for the unemployment rate using Moran plots. In this paper, in addition to Moran plots, the "leader-outsider" approach was used ([1] Oschepkov and Kapelyushnikov (2015). Considering the above-discussed relationship between unemployment rate and employment rate it is not surprising that in this paper, we obtain empirical results different from those of other studies focused on unemployment rates (e.g., [25] Danilenko et al., 2017).

3. Data and Variables

3.1 Data

Our sample consisted of 80 regions during the twelve-year period from 2005 to 2016. The majority of the data used in the research were available for public access via the website of the Federal State Statistics Service (FSSS) of the Russian Federation. It was impossible to include earlier years in the research due to the different classification of industries before the year 2005.

Table 1

United subjects of the Russian Federation

Data	Merging regions	Incorporated as
01.01.2007	Taymyr Autonomous Okrug	Krasnoyarsk Territory
	Evenk Autonomous Okrug	
	Krasnoyarsk territory	
01.07.2007	Kamchatka oblast	Kamchatka territory
	Koryak Autonomous Okrug	
01.01.2008	Ust-Orda Buryat Autonomous Okrug	Irkutsk region
	Irkutsk region	
01.03.2008	Chita region	Zabaykalsky Territory
	Aginsky Buryatsky Autonomous Okrug	
01.07.2012	Moscow, Moscow oblast	Moscow

Moreover, data on some regions were missing (the Republic of Chechnya, the Republic of Crimea and Sevastopol). In addition, the Kaliningrad region was not included in the study because it has no common borders with other regions of Russia. Moreover, during the reporting period, some regions underwent changes of an administrative-territorial nature. This altering of boundaries was taken into consideration, mitigated by an aggregating procedure (see Table 1).

3.2 The Splitting of Regions by Moran Plot

Russian regions are not homogeneous, and employment levels differ considerably among them. We distinguish a group of regions with an employment level above the average and a group of regions with a level of employment below the average. It is also necessary to take account of the weighted average employment rate in neighboring regions (the weights are given by the weighted matrix W matrix): it can also be above or below the average. Thus, we can distinguish four groups of regions. Traditionally used for such a division is the Moran chart, in which the horizontal axis states the standardized values of the employment rate Z, and the vertical axis states spatially weighted standardized values of the employment rate WZ.

In our analysis, a matrix of common borders was formed. It was represented by the following definition of W:

$$W_{cb} = \begin{pmatrix} 0 & w_{12}^{len} & \dots & w_{1n}^{len} \\ w_{21}^{len} & 0 & \dots & w_{2n}^{len} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}^{len} & w_{n2}^{len} & \dots & 0 \end{pmatrix}, \qquad (6)$$

$$\text{where } w_{ij}^{len} = \frac{\substack{\textit{length in km of jont boundaries} \\ \textit{between regions i and j}}}{\substack{\textit{total length in km} \\ \textit{of all boundaries of region i}}}.$$

We used information on the length of joint boundaries taken from the State real estate cadastre.[1] The matrix is line-normalized, so that w_{ij} accounts for the weights of a region; $w_{ij} = 0$, if there is no boundary between regions i and j or if $i = j$. For each region, we have a point on the Moran scatterplot which can be in one of four quarters. The first quarter represents the High–High group: this means that in the given region the employment rate is high and it is surrounded by regions also with high employment; it is a group of the most prosperous regions that positively influence each other. The second quarter represents the Low–High group: the employment rate in the region is low, but the neighbor region has a high level of employment; this is a group of disadvantaged regions that can receive some benefits from proximity to prosperous regions. The third quarter represents the Low–Low group: both the region and neighbors have low employment rates; this group comprises the most disadvantaged regions. The fourth quarter represents the High–Low group: the employment rate is high for the region and low for its neighbors; this is a group of prosperous regions, but the situation in them may worsen due to proximity to unfavorable regions.

We thus obtained scatterplots for each year from 2005 to 2016.[2] Each point was labeled by the number of the corresponding region. To determine the list of regions for each group, we counted how many times the corresponding points were in each quarter. We obtained the results set out in the table below.

It should be stressed that these groups of regions are close to, but not identical with, the group of four unemployment groups of regions in Russia discussed in [25] Danilenko et. al (2017).

In both cases, regions of LL group for employment and HH group for unemployment are geographically split into two parts: South of Russia and South of Siberia. We consequently decided to separate the *LL* (employment) group into two groups. Additionally, *HL* and *LH* groups contain, respectively, only 5 and 11 regions. We decided to add those regions to larger groups; to determine the destination group, we used the "leader-outsider" approach followed by [1] Oschepkov and Kapelyushnikov (2015, the details are in the next section).

3.3 The "Leader-Outsider" Approach

[1] Oschepkov and Kapelyushnikov (2015) concluded that regions had stable positions in time on all indicators considered. They distinguished between "leader" and "outsider" regions. High employment and purchasing power of nominal wages together with a low unemployment rate are observed in leading regions. By contrast, high unemployment and a low level of economic activity characterize "outsider" regions. The same authors highlight that it is possible to allocate leading and lagging regions to clusters by geographic location. In their analysis, the authors discussed only the first and last ten regions (leaders and outsiders). Moreover, they did not give the exact list of regions for each indicator.

Following the same approach of [1] Oschepkov and Kapelyushnikov (2015), we made a list of regions for three indicators: employment rate, unemployment rate, and the purchasing power of nominal wages using rankings. We took the data on the employment rate from 2005 to 2016 for each region from Table 2. Then, for each year, the regions were arranged in descending order by the employment rate and were ranked (the first region had rank 1, the second one rank 2, and so on). In the final list, the regions were arranged in ascending order by the mean rank for 12 years (the smallest mean rank corresponded to the region with the highest employment rate). The result was the list of regions that follows.

It should be noted that the list of leaders is almost the same for all three indicators. If we now consider Table 1 again, we find that regions from *HH* and *HL* groups are at the top of the list in Table 2, while regions from *LL* and *LH* groups are at its bottom.

Finally, according to the Moran plot for employment rate and "leader-outsider approach", the Russian regions were divided into 3 final groups. *HL* and *LH* groups were attached to the corresponding groups (*HL* + *HH*, *LH* + *LL*). The *LL* group was split into two clubs: *LL*1 group (South of Russia) and *LL*2 group (South of Siberia) by geographical criteria. Regions 40 and 54 were "outliers". To determine the relevant group, we calculated the mean value of the employment rate in those regions and clubs, and we joined "outliers"

[1] For the Sakhalin region these boundaries are measured by sea.

[2] Available upon request.

Table 2

List of employment groups

HH (High–High) Regions	*LL* (Low–Low) Regions	*LH* (Low–High) Regions
Vladimir region	Belgorod region	Bryansk region
Ivanovo region	Voronezh region	Orel region
Kaluga region	Kursk region	Ryazan region
Kostroma region	Tambov region	Republic of Bashkortostan
Smolensk region	Republic of Adygea	Penza region
Tver region	Republic of Kalmykia	Ulyanovsk region
Tula region	Krasnodar Territory	Kurgan region
Yaroslavl region	Astrakhan region	Tomsk region
Moscow	Volgograd region	Primorsky Territory
Republic of Karelia	Rostov region	Amur region
Republic of Komi	Republic of Dagestan	Jewish autonomous area
Arkhangelsk region	Republic of Ingushetia	
Nenets Autonomous Okrug	Republic of Kabardino-Balkaria	***HL* (High–Low) Regions**
Vologda region	Republic of Karachaevo-Cherkessia	Lipetsk region
Leningrad region	Republic of Northen Ossetia — Alania	Republic of Mordovia
Murmansk region	Stavropol Territory	Samara region
Novgorod region	Saratov region	Chelyabinsk region
Pskov region	Republic of Altay	Novosibirsk region
Saint-Petersburg	Republic of Buryatia	
Republic of Marii El	Republic of Tyva	
Republic of Tatarstan	Republic of Khakassia	
Republic of Udmurtia	Altay Territory	
Republic of Chuvashia	Zabaykalsky Territory	
Perm territory	Irkutsk region	
Kirov region	Kemerovo region	
Nizhny Novgorod region		
Orenburg region		
Sverdlovsk region		
Tumen region		
Khanty-Mansi Autonomous Area — Yugra		
Yamal-Nenets autonomous region		
Krasnoyarsk Territory		
Omsk region		
Republic of Sakha (Yakutia)		
Kamchatka territory		
Khabarovsk Territory		
Magadan region		
Sakhalin region		
Chukotka Autonomous Okrug		

with a group which had approximately the same mean. As a result, regions 40 and 54 were joined to the *LL*2 group.

The resulting division by employment groups is depicted below.

Regions from the *LL*1 group are mainly located in the south of Russia. These are mainly agricultural areas characterized by a high level of informal employment.

It should be noted that the authoritative experts on the Russian labor market in their report ([26] Gimpelson et al, 2017) also divide the Russian outsider regions into two groups: a group of southern republics and a group of regions of Southern Siberia (details can be found in [26]). They note that "the regions within each group have very similar structural and natural-geographical characteristics."

In previous research (see [25] Danilenko et al., 2017), we analyzed the difference in spatial effects and the determinants of unemployment rate for three clubs of Russian regions (*HH*, *LL*, *HL*). In the

Group	Color
HH	*Grey*
LL1	*Dark grey*
LL2	*Light grey*

Fig. *Employment groups*

Table 3

The list of Russian regions obtained by ranking

Employment (from highest to lowest level)	Unemployment (from lowest to highest level)	Buying power of nominal wage (from highest to lowest)
Chukotka Autonomous Okrug	Moscow	Nenets Autonomous Okrug
Yamal-Nenets Autonomous region	Saint-Petersburg	Yamal-Nenets Autonomous region
Magadan region	Chukotka Autonomous Okrug	Tumen region
Saint-Petersburg	Samara region	Khanty-Mansi Autonomous Area — Yugra
Moscow	Tula region	Chukotka Autonomous Okrug
Khanty-Mansi Autonomous Area — Yugra	Yamal-Nenets Autonomous region	Magadan region
Murmansk region	Lipetsk region	Moscow
Kamchatka territory	Belgorod region	Saint-Petersburg
Tumen region	Republic of Mordovia	Sakhalin region
Nenets Autonomous Okrug	Yaroslavl region	Republic of Komi
Leningrad region	Novgorod region	Krasnoyarsk Territory
Samara region	Kostroma region	Murmansk region
Kaluga region	Kaluga region	Republic of Sakha (Yakutia)
Sakhalin region	Leningrad region	Kemerovo region
Republic of Mordovia	Magadan region	Irkutsk region
Yaroslavl region	Republic of Tatarstan	Tomsk region
Republic of Udmurtia	Tver region	Kamchatka territory
Kostroma region	Nizhny Novgorod region	Arkhangelsk region
Novgorod region	Ryazan region	Republic of Tatarstan
Vologda region	Penza region	Sverdlovsk region

Continued table 3

Employment (from highest to lowest level)	Unemployment (from lowest to highest level)	Buying power of nominal wage (from highest to lowest)
Nizhny Novgorod region	Chelyabinsk region	Zabaykalsky Territory
Sverdlovsk region	Tumen region	Leningrad region
Krasnoyarsk Territory	Ivanovo region	Republic of Karelia
Vladimir region	Voronezh region	Chelyabinsk region
Tver region	Vologda region	Omsk region
Republic of Tatarstan	Kursk region	Republic of Bashkortostan
Smolensk region	Arkhangelsk region	Republic of Khakassia
Kirov region	Krasnodar Territory	Kaluga region
Lipetsk region	Vladimir region	Amur region
Khabarovsk Territory	Orel region	Vologda region
Arkhangelsk region	Sverdlovsk region	Belgorod region
Chelyabinsk region	Khanty-Mansi Autonomous Area — Yugra	Khabarovsk Territory
Republic of Sakha (Yakutia)	Bryansk region	Novosibirsk region
Republic of Komi	Ulyanovsk region	Novgorod region
Republic of Karelia	Orenburg region	Republic of Tyva
Tula region	Republic of Bashkortostan	Astrakhan region
Republic of Chuvashia	Krasnoyarsk Territory	Yaroslavl region
Ivanovo region	Smolensk region	Republic of Buryatia
Astrakhan region	Stavropol Territory	Lipetsk region
Perm territory	Khabarovsk Territory	Tula region
Primorsky Territory	Amur region	Orenburg region
Pskov region	Saratov region	Perm territory
Republic of Marii El	Rostov region	Republic of Udmurtia
Novosibirsk region	Novosibirsk region	Primorsky Territory
Belgorod region	Tambov region	Nizhny Novgorod region
Orenburg region	Sakhalin region	Saratov region
Kursk region	Kamchatka territory	Krasnodar Territory
Irkutsk region	Pskov region	Samara region
Omsk region	Kirov region	Jewish Autonomous area
Orel region	Nenets Autonomous Okrug	Tver region
Kemerovo region	Republic of Udmurtia	Volgograd region
Ulyanovsk region	Perm territory	Penza region
Volgograd region	Volgograd region	Smolensk region
Amur region	Murmansk region	Orel region
Republic of Bashkortostan	Kemerovo region	Ryazan region
Bryansk region	Republic of Karelia	Kostroma region
Saratov region	Omsk region	Rostov region
Tomsk region	Republic of Khakassia	Kursk region
Republic of Northen Ossetia — Alania	Primorsky Territory	Republic of Chuvashia
Rostov region	Republic of Chuvashia	Vladimir region
Penza region	Altay Territory	Republic of Marii El
Krasnodar Territory	Tomsk region	Ulyanovsk region
Altay Territory	Republic of Marii El	Pskov region
Republic of Khakassia	Republic of Sakha (Yakutia)	Republic of Ingushetia
Ryazan region	Jewish Autonomous area	Kurgan region
Voronezh region	Astrakhan region	Voronezh region
Republic of Altay	Republic of Komi	Bryansk region
Stavropol Territory	Republic of Adygea	Kirov region
Tambov region	Republic of Northen Ossetia — Alania	Republic of Mordovia

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End of table 3

Employment (from highest to lowest level)	Unemployment (from lowest to highest level)	Buying power of nominal wage (from highest to lowest)
Jewish Autonomous area	Irkutsk region	Tambov region
Kurgan region	Zabaykalsky Territory	Republic of Northen Ossetia — Alania
Republic of Kalmykia	Kurgan region	Stavropol Territory
Zabaykalsky Territory	Republic of Buryatia	Republic of Adygea
Republic of Karachaevo-Cherkessia	Republic of Altay	Altay Territory
Republic of Buryatia	Republic of Karachaevo-Cherkessia	Republic of Altay
Republic of Adygea	Republic of Kabardino-Balkaria	Republic of Kabardino-Balkaria
Republic of Dagestan	Republic of Dagestan	Ivanovo region
Republic of Kabardino-Balkaria	Republic of Kalmykia	Republic of Karachaevo-Cherkessia
Republic of Tyva	Republic of Tyva	Republic of Kalmykia
Republic of Ingushetia	Republic of Ingushetia	Republic of Dagestan

Table 4

List of regions with numbers

Number	Region	Number	Region
1	Belgorod region	41	Republic of Marii El
2	Bryansk region	42	Republic of Mordovia
3	Vladimir region	43	Republic of Tatarstan
4	Voronezh region	44	Republic of Udmurtia
5	Ivanovo region	45	Republic of Chuvashia
6	Kaluga region	46	Perm territory
7	Kostroma region	47	Kirov region
8	Kursk region	48	Nizhny Novgorod region
9	Lipetsk region	49	Orenburg region
10	Orel region	50	Penza region
11	Ryazan region	51	Samara region
12	Smolensk region	52	Saratov region
13	Tambov region	53	Ulyanovsk region
14	Tver region	54	Kurgan region
15	Tula region	55	Sverdlovsk region
16	Yaroslavl region	56	Tumen region
17	Moscow	57	Khanty-Mansi Autonomous Area — Yugra
18	Republic of Karelia	58	Yamal-Nenets autonomous region
19	Republic of Komi	59	Chelyabinsk region
20	Arkhangelsk region	60	Republic of Altay
21	Nenets Autonomous Okrug	61	Republic of Buryatia
22	Vologda region	62	Republic of Tyva
23	Leningrad region	63	Republic of Khakassia
24	Murmansk region	64	Altay Territory
25	Novgorod region	65	Zabaykalsky Territory
26	Pskov region	66	Krasnoyarsk Territory
27	Saint-Petersburg	67	Irkutsk region
28	Republic of Adygea	68	Kemerovo region
29	Republic of Kalmykia	69	Novosibirsk region
30	Krasnodar Territory	70	Omsk region
31	Astrakhan region	71	Tomsk region
32	Volgograd region	72	Republic of Sakha (Yakutia)
33	Rostov region	73	Kamchatka territory
34	Republic of Dagestan	74	Primorsky Territory
35	Republic of Ingushetia	75	Khabarovsk Territory
36	Republic of Kabardino-Balkaria	76	Amur region

End of table 4

Number	Region	Number	Region
37	Republic of Karachaevo-Cherkessia	77	Magadan region
38	Republic of Northen Ossetia — Alania	78	Sakhalin region
39	Stavropol Territory	79	Jewish autonomous area
40	Republic of Bashkortostan	80	Chukotka Autonomous Okrug

research reported here, we decided to test similar hypotheses for three employment groups.

H1: spatial effects for the *HH*, *LL*1, and *LL*2 groups differ;

H2: the determinants of employment for the *HH*, *LL*1, and *LL*2 groups differ.

3.4 The Data, the Dependent and the Explanatory Variables

As said, our sample consisted of 80 regions. Due to data availability, the employment rate was calculated on the population aged between 15 to 72.

To explain existing levels of employment rate (variable *empl*.) and to test two research hypotheses, three groups of variables were chosen: 1) variables concerning the attractiveness of the region; 2) socio-demographic variables; and 3) variables concerning the industrial structure of the employed population. The first group of variables consisted of four indicators: (i) *GRP* per capita (variable *grppercap*_1, thousand rubles in prices of basic year), (ii) population density (variable *density*, people per square km), (iii) the share of urban population (variable *urban_share*, %), (iv) net migration rate (*migration*_1, number of migrants per 10 000 population, may be positive or negative). The socio-demographic features of the population consisted of variables characterizing the age structure of the population and the stock of human capital. To illustrate the age structure, the shares of people below and above working age were taken as variables (*below* and *above*, %). Working age in Russia is above 16 and below retirement age, which was 60 years for men and 55 for women during the studied period. The stock of human capital was measured as the share of the employed population with a higher education (variable *high_educ*, %), where 'higher education' means that someone has at least a higher professional education according to the FSSS classification. The sectoral structure is one of the most important features in explaining the regional employment rate. Consequently, we used the Hirschman-Herfindahl Index (variable *hh*_1) to characterize the industrial structure of each region; and it is used as a measure of the region's degree of sectoral specialization.

$$HHI = S_1^2 + S_2^2 + \ldots + S_n^2, \quad (7)$$

where $S_1^2, S_2^2, \ldots, S_n^2$ are shares of people employed in sectors of economic activity (agriculture, construction, wholesale and retail trade, public sector (consisting of education and health services), mining, manufacturing, services). The region is more monopolized if the *hh* value is closer to 1.

To avoid the problem of endogeneity, we used the first time lag of the variables *grp*, *migration*, *hh*.

We now compare the descriptive statistics of variables for different groups (see Table 4).

There are disparities between *HH*, *LL*1 and *LL*2 groups. For example, almost all mean values for variables that characterize the attractiveness of the region are higher in the *HH* group.

4. Methodology of the Econometric Modeling

To test the two main research hypotheses, we used the following modification of the SAR (Spatial Auto Regression) model:

$$\begin{pmatrix} Y_{iH} \\ Y_{iL1} \\ Y_{iL2} \end{pmatrix}_t = \tau \begin{pmatrix} Y_{iH} \\ Y_{iL1} \\ Y_{iL2} \end{pmatrix}_{t-1} + \rho_H \begin{pmatrix} WY_{iH} \\ 0 \\ 0 \end{pmatrix}_t + \rho_{L1} \begin{pmatrix} 0 \\ WY_{iL1} \\ 0 \end{pmatrix}_t + \rho_{L2} \begin{pmatrix} 0 \\ 0 \\ WY_{iL2} \end{pmatrix}_t + \begin{pmatrix} X_{iH} \\ 0 \\ 0 \end{pmatrix}_t \beta_H + \begin{pmatrix} 0 \\ X_{iL1} \\ 0 \end{pmatrix}_t \beta_{L1} + \begin{pmatrix} 0 \\ 0 \\ X_{iL2} \end{pmatrix}_t \beta_{L2} + \begin{pmatrix} \alpha_{iH} \\ \alpha_{iL1} \\ \alpha_{iL2} \end{pmatrix} + c_t + \begin{pmatrix} u_{iH} \\ u_{iL1} \\ u_{iL2} \end{pmatrix}_t, \quad (8)$$

where Y is employment in group 15–72, WY is spatial lag, X is a matrix of explanatory variables, α is a vector of fixed effects, u is a vector of errors (we split them in three parts), c is a vector of time effects (set of dummy variables for 2007–2016 years).

Let us formulate our hypotheses in a form convenient for empirical verification:

Hypothesis 1. There are no differences of spatial effects in regional groups.

Alternative hypothesis 1. There are differences of spatial effects in regional groups.

Table 5

Descriptive statistics for the variables

Variable		Mean	Std. Dev.	Min	Max	Observations
All Russia						
empl	overall	62.528	5.955	16.500	81.200	$N = 960$
	between		5.505	34.475	78.783	$n = 80$
	within		2.345	44.553	78.853	$T = 12$
wcbempl	overall	62.939	3.777	36.439	78.836	$N = 960$
	between		3.386	46.110	76.357	$n = 80$
	within		1.713	53.267	73.657	$T = 12$
widempl	overall	62.138	2.427	41.332	65.947	$N = 960$
	between		1.836	49.799	64.295	$n = 80$
	within		1.600	53.671	70.136	$T = 12$
grppercap_1	overall	96963.860	117139.900	2133.539	1035858.000	$N = 960$
	between		101129.200	11439.280	589271.300	$n = 80$
	within		60099.540	−387423.000	543550.500	$T = 12$
urbanshare	overall	0.694	0.126	0.260	1.000	$N = 960$
	between		0.126	0.278	1.000	$n = 80$
	within		0.011	0.653	0.738	$T = 12$
below	overall	17.701	3.548	12.100	34.400	$N = 960$
	between		3.450	13.025	31.158	$n = 80$
	within		0.907	15.243	20.943	$T = 12$
above	overall	21.397	4.931	5.500	30.200	$N = 960$
	between		4.638	8.258	28.125	$n = 80$
	within		1.747	16.905	27.805	$T = 12$
migration_1	overall	−9.754	54.749	−499.000	197.000	$N = 960$
	between		43.594	−142.333	107.500	$n = 80$
	within		33.449	−492.338	172.079	$T = 12$
density	overall	73.322	387.276	0.069	3752.572	$N = 960$
	between		388.906	0.070	3482.613	$n = 80$
	within		21.661	−146.362	343.280	$T = 12$
high_educ	overall	26.654	5.678	12.500	50.000	$N = 960$
	between		4.443	18.925	47.758	$n = 80$
	within		3.567	14.671	40.521	$T = 12$
hh_1	overall	0.293	0.060	0.204	0.635	$N = 960$
	between		0.056	0.215	0.557	$n = 80$
	within		0.023	0.196	0.560	$T = 12$
***HH* group**						
empl	overall	65.681	3.855	57.700	81.200	$N = 528$
	between		3.417	61.800	78.783	$n = 44$
	within		1.853	58.898	70.748	$T = 12$
wcbempl	overall	64.648	2.691	58.622	78.836	$N = 528$
	between		2.341	60.473	76.357	$n = 44$
	within		1.369	60.239	67.666	$T = 12$
widempl	overall	62.897	1.521	59.289	65.947	$N = 528$
	between		0.598	61.473	64.295	$n = 44$
	within		1.401	59.961	65.113	$T = 12$
grppercap_1	overall	124489.100	146080.500	2133.539	1035858.000	$N = 528$
	between		125809.100	34761.040	589271.300	$n = 44$
	within		76432.750	−359897.800	571075.700	$T = 12$
urbanshare	overall	0.755	0.095	0.573	1.000	$N = 528$
	between		0.096	0.588	1.000	$n = 44$
	within		0.011	0.715	0.800	$T = 12$
below	overall	16.929	2.629	12.100	24.800	$N = 528$
	between		2.501	13.025	23.858	$n = 44$
	within		0.887	15.496	19.288	$T = 12$

Continued table 5

Variable		Mean	Std. Dev.	Min	Max	Observations
above	overall	21.580	5.011	5.500	30.200	$N = 528$
	between		4.704	8.258	28.125	$n = 44$
	within		1.855	17.089	27.989	$T = 12$
migration_1	overall	–7.242	57.181	–223.000	197.000	$N = 528$
	between		48.814	–142.333	107.500	$n = 44$
	within		30.604	–190.325	174.591	$T = 12$
density	overall	107.836	519.274	0.069	3752.572	$N = 528$
	between		523.951	0.070	3482.613	$n = 44$
	within		29.178	–111.848	377.794	$T = 12$
high_educ	overall	26.414	6.174	12.500	50.000	$N = 528$
	between		5.142	19.035	47.758	$n = 44$
	within		3.497	14.431	35.189	$T = 12$
hh_1	overall	0.291	0.069	0.205	0.635	$N = 528$
	between		0.064	0.215	0.557	$n = 44$
	within		0.028	0.193	0.558	$T = 12$
***LL*1 group**						
empl	overall	58.474	6.710	16.500	67.300	$N = 264$
	between		5.966	34.475	62.725	$n = 22$
	within		3.306	40.499	74.799	$T = 12$
wcbempl	overall	60.236	4.420	36.439	67.223	$N = 264$
	between		3.800	46.110	64.996	$n = 22$
	within		2.387	50.565	70.954	$T = 12$
widempl	overall	60.688	3.500	41.332	65.159	$N = 264$
	between		2.887	49.799	63.220	$n = 22$
	within		2.064	52.221	68.686	$T = 12$
grppercap_1	overall	59339.110	43394.850	3310.776	291518.000	$N = 264$
	between		35287.700	11439.280	161948.200	$n = 22$
	within		26267.330	–33631.360	188908.800	$T = 12$
urbanshare	overall	0.608	0.106	0.384	0.767	$N = 264$
	between		0.108	0.413	0.760	$n = 22$
	within		0.011	0.580	0.644	$T = 12$
below	overall	17.756	4.102	13.600	33.400	$N = 264$
	between		4.127	14.233	30.425	$n = 22$
	within		0.713	15.431	20.731	$T = 12$
above	overall	22.358	4.960	7.600	29.900	$N = 264$
	between		4.839	9.408	27.592	$n = 22$
	within		1.472	19.533	26.474	$T = 12$
migration_1	overall	–2.585	55.750	–499.000	148.000	$N = 264$
	between		37.061	–86.667	75.833	$n = 22$
	within		42.332	–485.169	161.832	$T = 12$
density	overall	45.202	26.455	3.726	143.530	$N = 264$
	between		26.944	3.803	130.743	$n = 22$
	within		2.066	29.739	57.989	$T = 12$
high_educ	overall	28.120	4.833	16.600	46.000	$N = 264$
	between		3.054	23.233	36.417	$n = 22$
	within		3.797	17.461	41.986	$T = 12$
hh_1	overall	0.308	0.045	0.238	0.456	$N = 264$
	between		0.043	0.253	0.433	$n = 22$
	within		0.016	0.268	0.406	$T = 12$
***LL*2 group**						
empl	overall	58.990	3.977	45.800	65.900	$N = 168$
	between		3.625	48.225	62.917	$n = 14$
	within		1.882	52.032	62.932	$T = 12$

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End of table 5

Variable		Mean	Std. Dev.	Min	Max	Observations
wcbempl	overall	61.815	2.500	55.573	67.400	$N = 168$
	between		2.143	57.311	64.955	$n = 14$
	within		1.399	57.884	64.857	$T = 12$
widempl	overall	62.032	1.441	59.104	65.172	$N = 168$
	between		0.559	61.020	63.062	$n = 14$
	within		1.336	59.455	64.142	$T = 12$
grppercap_1	overall	69580.570	55707.250	5249.425	309864.000	$N = 168$
	between		44904.770	21177.230	170118.100	$n = 14$
	within		34923.890	–35537.610	209326.500	$T = 12$
urbanshare	overall	0.637	0.135	0.260	0.858	$N = 168$
	between		0.139	0.278	0.853	$n = 14$
	within		0.013	0.611	0.663	$T = 12$
below	overall	20.042	4.072	15.400	34.400	$N = 168$
	between		4.026	16.117	31.158	$n = 14$
	within		1.200	17.584	23.284	$T = 12$
above	overall	19.310	3.960	9.200	28.500	$N = 168$
	between		3.648	9.958	24.833	$n = 14$
	within		1.803	16.377	22.977	$T = 12$
migration_1	overall	–28.917	39.109	–159.000	79.000	$N = 168$
	between		30.738	–80.000	28.917	$n = 14$
	within		25.435	–126.167	46.833	$T = 12$
density	overall	9.036	9.080	0.750	29.660	$N = 168$
	between		9.332	1.852	28.982	$n = 14$
	within		1.047	0.628	10.968	$T = 12$
high_educ	overall	25.107	4.697	14.500	36.200	$N = 168$
	between		3.320	18.925	30.842	$n = 14$
	within		3.430	15.490	32.707	$T = 12$
hh_1	overall	0.277	0.043	0.204	0.371	$N = 168$
	between		0.042	0.217	0.352	$n = 14$
	within		0.015	0.247	0.322	$T = 12$

Formal main and alternative hypotheses 1:

$$H_0 : \rho_H = \rho_{L1} = \rho_{L2},$$
$$H_1 : \rho_H \neq \rho_{L1} \text{ or } \rho_H \neq \rho_{L2}.$$

Hypothesis 2. There are no differences in the influence of the factors on employment rates in the regions belonging to different regional clubs.

Alternative hypothesis 2. There are differences in the influence of the factors on employment rates in the regions belonging to different regional clubs.

Formal main and alternative hypotheses 2:

$$H_0 : \beta_H = \beta_{L1} = \beta_{L2},$$
$$H_1 : \beta_H \neq \beta_{L1} \text{ or } \beta_H \neq \beta_{L2}.$$

The split spatial lags in our model were endogenous. To resolve the problem of endogeneity difference, we adopted the GMM ([27] Arellano and Bond, 1991) method of estimation. However, application of this method to our initial specification (with all explanatory variables, divided into several parts) required a number of instruments much larger than the number of regions. According to Roodman (2009), this leads to a bias in the parameter estimation. To avoid this problem we had to use the Arellano-Bond approach for the estimation and drastically restrict the number of instruments. Moreover, in order to consider the possible bias in the parameters' estimation at a small time interval but with a large number of observation units, we adopted a GMM modification for models with fixed effects, similarly to [28] Lee and Yu (2010). In addition, a large number of variables may also lead to the problem of multicollinearity of the data. To increase the efficiency of the estimates, we removed groups of insignificant variables from the model one by one (after a preliminary test of the corresponding statistical hypotheses). The technique that we used was an extension of the conventional backward stepwise method. To test the robustness of the result of the estimation, we re-estimated our model with an inverted distance weighted matrix instead of the matrix of common borders. The results of the estimation are presented in the next section.

5. TheResults of the Estimation

In this section, we present the final results of our main estimations (Table 6). For each model, we also present the results of post-estimation procedures. Estimates of the coefficients obtained by the Arellano-Bond method are consistent under the following conditions ([29] Greene, 2012, p. 400): 1) errors u_{it} must be serially uncorrelated; 2) moment conditions (consisting in the orthogonality of the errors and instruments) must be correct. The Arellano-Bond approach, using the equations in difference, makes it possible to avoid the endogeneity problem with the elimination of individual effects. It is for this reason that the errors in the difference equation must be identified as first-order autocorrelations and not revealed as higher-order autocorrelations (Arellano and Bond test). The second condition is verified by the Sargan test of instruments' validity. These two conditions are verified for all the models estimated.

Spatial effects for the three employment groups were different. For the *LL*2 group of regions, the spatial effects were insignificant; hence employment in the regions of the *LL*2 group does not depend on the local labor markets of other regions. For the group of *HH* regions, only spatial effects for the inverse distance weighting matrix are significant. Consequently, each region of the *HH* group is affected by the rest of Russia's regions, and the extent of this influence decreases with the increase in geographical distance between regions. Employment in the *HH* region group varies according to the general situation in the country.

The most interesting spatial effects were revealed for the regions in the *LL*1 group. For a common boundary weighting matrix, they were negative, and for a weighting matrix of inverted distances, they were positive. Thus, in the *LL*1 group of regions (in the south of Russia), there is a mechanism of competition for labor resources with neighboring regions. If in one of the southern regions the situation on the labor market improves, then it draws labor resources from neighboring regions. At the same time, if the overall employment situation in Russia improves (or worsens), then similar changes occur in the *LL*1 group of regions.

In regard to the impact of the explanatory variables, the "group effect" was found for the variables share of urban population, net migration rate, shares of people below and above working age, share of people with higher education.

The influences of *GRP* per capita and on the level of employment was insignificant.

For *LL*2 and *HH* groups of regions, employment was not dependent on the share of the urban population. This can be explained by the presence of two opposite tendencies: in a city, it is usually easier to find a job; but for monotowns, of which there are more than 300 in Russia when the city-forming enterprise closes, the situation changes to the op-

Table 6

The results of estimation

Dependent Variable empl	**modelwcb**	**modelwid**
Weighted matrix	Matrix of common borders	Matrix of inverted distance
empl		
L1. (time lag)	0.562^{***}	0.553^{***}
Spatial lags		
wcbempL1	-0.184^{***}	
wcbempL2	0.105	
wcbemplH	0.125	
widempL1		0.101^{*}
widempL2		0.234
widemplH		0.391^{***}
urbanshareL1	-51.186^{***}	-29.216^{***}
belowL1	-1.017^{***}	-0.785^{***}
belowL2	-0.415^{**}	–0.139
belowH	-0.373^{**}	–0.154
aboveL1	0.821^{***}	0.813^{***}
migr_1L1	0.006^{***}	0.007^{***}
migr_1L2	0.006^{*}	0.004
migr_1H	-0.007^{***}	-0.006^{***}
dens	-0.004^{***}	-0.003^{*}
high_edL2	0.129^{**}	0.147^{**}
hh_1	5.017^{*}	4.857^{*}
d2007	0.206	0.239
d2008	–0.164	–0.332
d2009	-1.188^{***}	-1.138^{***}
d2010	0.175	–0.062
d2011	0.583	0.122
d2012	1.237^{***}	0.338
d2013	0.698	–0.235
d2014	1.272^{**}	0.095
d2015	0.992^{*}	–0.206
d2016	1.301^{**}	–0.098
_cons	35.103^{***}	11.964^{*}
Number of instruments	62	62
p-v AB test for zero autocorrelation		
in first-differenced errors		
order 1	0.000	0.000
order 2	0.133	0.12
p-v Sargan test	0.477	0.254

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

posite.[1] The increase in the share of urban population reduced employment in the Low-Low1 group. This can be explained by the fact that a large proportion of businesses in the southern regions are engaged in agriculture.

With an increase in the population aged under 16, the level of employment was reduced according to both estimated models only in the *LL*1 group of regions. This can be explained by the fact that in the North Caucasus regions that belong to this group, the share of young people is very high, and for them, it is difficult to find jobs. Conversely, increasing the proportion of the population over working age increases employment in the *LL*1 group, because in these regions there are relatively low wages; therefore, on reaching retirement age, people often leave the labor market, preferring informal employment and work on personal plots of land.

The influx of migrants stimulates employment in the *LL*1 group of regions and decreases employment in the group of *HH* regions. This may be because more educated migrants able to compete for well-paid jobs go mainly to the regions of the *HH* group.

An increase in the proportion of the population with higher education stimulates employment only in the *LL*2 group of regions.

Group effects were not found for the variables density and Herfindahl-Hirschman index.

The negative dependence of employment on population density can be explained 1) by competition for jobs, 2) by the problem of monotowns mentioned above, 3) by the favorable situation in the labor markets of some sparsely populated northern regions. Perhaps, for this variable, a functional dependence more flexible than the linear one should be used.

A higher Herfindahl-Hirschman index is associated with higher employment. The higher the Herfindahl-Hirschman index, the more the level of specialization in the given region. Thus, in 2005–2016 in Russia Marshallian effects prevailed.

The results of the estimation also make it possible to draw a conclusion about the negative impact of the 2008–2009 crisis on the level of employment, whereas the crisis of 2014 did not affect it. This is probably because the 2008–2009 crisis was global, while the crisis in 2014 had a local character with effects more delayed and distributed over time.

6. Conclusions

In this paper, we have investigated the spatial effects for the regional employment groups in Russia and the differences in the impact factors that explain regional employment. The key results are the following: (1) boundary spatial effects for three groups are different; (2) the differing influence for selected groups of regions was apparent for the share of urban population, net migration rate, the shares of people below and above working age, the share of people with higher education; (3) the influence of GRP is insignificant.

According to our results, these are several (general and specific) policy implications. From a general perspective, (national and regional) economic and labor policies must take the specificity of each group of regions into account; in fact, the same policy measures can generate significantly different consequences in *HH*, *LL*1 and *LL*2 groups of regions; moreover, policies should consider that the (positive) impact on a group of regions can indirectly (negatively or positively) affect other groups of regions. As regards the specific policy implications, the following aspects seem most important: (i) policies favoring a higher level of specialization are suggested due to the positive employment effects in all groups of regions; (ii) an increase of the higher educated proportion of the labor force is recommended because it would increase employment in the South of Siberia and in Zabaikalye; (iii) the increase in migration flows favorably affects the employment of only the *LL*1 group of regions, where the agricultural sector is well developed; therefore, it is desirable to create favorable conditions for migrants in the South of Russia, while in more densely populated regions of Russia, migrants can compete for jobs with indigenous people, worsening both wage and working conditions; (iv) national and regional economic, educational and labor policies could focus especially on improving the dramatic employment quantity and quality in the group of regions *LL*1, especially considering the supply-demand mismatches and the difficulties of transition — from education and from unemployment — to employment, also reducing the problem of competing for resources with neighboring regions.

These results are consistent with the findings of the report based on [26] that federal policy in the labor market in Russia should be built with "possible consideration of the heterogeneity of the regions", there are no "simple and quick solutions" to smoothing the differentiation of Russian regions, this problem requires a "strategic and integrated approach."

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